

DCAFE: Dynamic load-balanced loop Chunking & Aggressive Finish Elimination for Recursive Task Parallel Programs

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In this paper, we present two symbiotic optimizations to optimize recursive task parallel (RTP) programs by reducing the task creation and termination overheads. Our first optimization Aggressive Finish-Elimination (AFE) helps reduce the redundant join operations to a large extent. The second optimization Dynamic Load-Balanced loop Chunking (DLBC) extends the prior work on loop chunking to decide on the number of parallel tasks based on the number of available worker threads, at runtime. Further, we discuss the impact of exceptions on our optimizations and extend them to handle RTP programs that may throw exceptions. We implemented DCAFE (= DLBC+AFE) in the X10v2.3 compiler and tested it over a set of benchmark kernels on two different hardware (a 16-core Intel system and a 64-core AMD system). With respect to the base X10 compiler extended with loop-chunking of Nandivada et al [Nandivada et al.(2013)Nandivada, Shirako, Zhao, and Sarkar] (LC), DCAFE achieved a geometric mean speed up of $5.75\times$ and $4.16\times$ on the Intel and AMD system, respectively. We also present an evaluation with respect to the energy consumption on the Intel system and show that on average, compared to the LC versions, the DCAFE versions consume 71.2% less energy.

Categories and Subject Descriptors: D.3.4 [Programming Languages]: Processors—Optimization; Compilers; Parallelism

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1. INTRODUCTION

The onset of multi-core architectures has brought forth a shift in programming paradigm from sequential programs to parallel programs. This shift has led to an increased interest in task parallel languages, such as X10 [Saraswat et al.(2012)Saraswat, Bard, Igor, Tardieu, and Grove], Chapel [Chamberlain et al.(2007)Chamberlain, Callahan, and Zima], OpenMP [OpenMP(2008)], HJ [Cavé et al.(2011)Cavé, Zhao, Shirako, and Sarkar], and so on. These languages allow the programmer to express the desired amount of parallelism (a.k.a *ideal* parallelism), while delegating the task of extracting the *useful* parallelism to the compiler (or runtime). In this paper, we present two novel compiler optimizations (targeting recursive task parallel programs) to extract useful parallelism from the ideal.

New paper, Not an extension of a conference paper.

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```

1 def find_queens() {
2   ...
3   nqueens (n, 0, ...); }

4 def nqueens (val n:Int, val j:Int, ...) {
5   finish {
6     for (var i:Int=0; i<n; i++) {
7       async {
8         ... /* Checking if none of the queens conflict */
9         nqueens (n, j+1, ...); } } } }
10  (a)

4 def nqueens (val n:Int, val j:Int, ...) {
5   var nChunks: Int = Runtime.getRuntime().getAvailableProcessors();
6   var chunkSize: Int = (n+nChunks-1)/nChunks;
7   finish {
8     for (var ii:Int=0; ii<n; ii+=chunkSize) {
9       val ni = ii;
10      async {
11        var kx: Int = ni+chunkSize;
12        if (kx>n) kx=n;
13        for (var i:Int=ni; i<kx; i++) {
14          ... /* Checking if none of the queens conflict */
15          nqueens (n, j+1, ...); } } } } }
16  (b)

```

Fig. 1: BOTS Nqueens kernel in X10: (a) Unoptimized version (b) Loop Chunked version of the nqueens function.

Recursive Task Parallel (RTP) programs constitute an important subset of task parallel programs. In RTP programs the parent task spawns a set of child tasks, which in turn can recursively spawn further tasks. This renders the problem of extracting useful parallelism from the ideal quite challenging in case of RTP programs (compared to non-RTP programs). We will use an example to illustrate the same.

Figure 1(a) shows the snippet of the BOTS [Duran et al.(2009)Duran, Teruel, Ferrer, Martorell, and Ayguade] Nqueens kernel, in X10. The `async` construct spawns a new child task to execute the statement within its body, in parallel with the parent task. The `finish` construct acts as a join point for all the tasks spawned in its body. The code in Figure 1(a) shows that the presence of recursive task parallelism may lead to the execution of a large number of `finish` operations at runtime (for example, when $n=14$, it executes 27 million `finish` operations). Prior work [Nandivada et al.(2013)Nandivada, Shirako, Zhao, and Sarkar] shows that eliminating unnecessary `finish` operations can lead to significant performance improvements. However, their proposed technique does not lead to any reduction in the number of `finish` operations, in this example. Interestingly, we observe that each task spawns new child tasks, and waits at the join point for the spawned tasks to terminate. After that the task simply returns from the procedure. Hence, this `finish` construct can be pulled out of the `nqueens` method and placed around its non-recursive call site (in `find_queens`). Or in other words, the `finish` construct, in the method `nqueens` can be declared redundant (and hence removed), if we surround the non-recursive call to `nqueens` with a `finish` construct. Such an optimization helps us in reducing the number of `finish` operations to just one (for this code), which can lead to significant performance gains.

In general, it is not trivial to pull out `finish` constructs, as they may be nested deep inside some `if/while` constructs. The problem becomes further challenging, if the input code may throw exceptions. We address these challenges in the first optimization we propose in this paper (called *Aggressive Finish-Elimination*, or *AFE* in short). AFE helps to eliminate redundant `finish` operations in RTP programs, in a semantics preserving way.

Further analysis of Figure 1(a) shows that at the k^{th} level of recursion, the `nqueens` function creates n^k number of `asyncs` (tasks) leading to an explosion of tasks (for example, when $n=14$, it creates a total of 377 million tasks), which in turn results in large performance overheads. The powerful scheme of Loop Chunking [Nandivada et al.(2013)Nandivada, Shirako, Zhao, and Sarkar] (henceforth referred to as LC) helps to extract useful parallelism from the ideal. LC splits the iterations of a large parallel loop into a set of chunks, where each chunk (containing a set of serial iterations) executes in parallel.

Figure 1(b) presents the LC version of the `nqueens` function. Here, the call to the `Runtime.retNthreads` function returns the initial count of the worker threads. Hence, the useful parallelism is bound by `nChunks`. Considering this, LC ensures that at most `nChunks` number of tasks are created in any invocation of this function. Thus, at level k of recursion, it creates $nChunks^k$ number of tasks (for example, when $n=14$ and `nChunks=8`, it creates 189 million tasks). This chunked program runs faster than the unoptimized version, but still incurs a large task creation and termination overhead. This is because the chunking algorithm is oblivious to the recursive call inside the loop, and hence, permits the spawning of a large number of tasks. We have observed a similar trend in a number of RTP kernels present in two open-sourced benchmark suites: IMSuite [Gupta and Nandivada(2015)] and BOTS.

The main reason for the LC version to incur the large overheads is that it does not exploit the underlying recursive nature of the task parallel program and misses significant opportunities to optimize such programs. To address this challenge, we propose our second optimization “Dynamic Load-Balanced loop Chunking” (DLBC), as an extension to LC. DLBC generates code that spawns new tasks (to execute some iterations of a loop) only if “idle” workers are available, at runtime. Otherwise, the current worker executes the loop serially. During the serial execution, if some workers get freed up, the remaining loop iterations may be executed in parallel (by the available workers). Our transformation leads to significant reduction in the number of tasks created: for example, for Figure 1(a), when $n=14$, our *transformed* code creates 6 million tasks ($\approx 30\times$ less, compared to the LC version).

Realising the above mentioned extensions requires multiple design choices (e.g., how to identify the number of available workers, how to divide work among the current and available workers, when to execute the code in the serial mode, when to switch back to parallel execution, and so on), that are non-trivial in nature. We studied many different design alternatives and designed DLBC using the best available choices.

Our Contributions

- We propose two symbiotic optimizations AFE and DLBC, for improving the performance of RTP programs that reduce the redundant join and task creation operations. DCAFE (= DLBC + AFE) can be easily extended to other task parallel languages (such as HJ, Chapel and OpenMP) that have similar constructs for task creation and task termination operations.
- We present an extension to the X10v2.3 compiler that implements DCAFE.
- We extend DCAFE to perform semantics preserving code transformation even in the presence of exceptions.
- We evaluated DCAFE over 8 benchmarks (drawn from two benchmark suites: IMSuite and BOTS) on two different hardware systems (a 16-core Intel system and a 64-core AMD system). We show that DCAFE leads to improved execution times (geometric mean of $5.75\times$ on the Intel and $4.16\times$ on the AMD system, with respect to the LC version; and geometric mean of $12.64\times$ on the Intel and $5.25\times$ on the AMD system, with respect to the unoptimized version).
- We also show that the use of DCAFE leads to significantly lower energy consumption, on the Intel system. On average, DCAFE optimized codes consume $0.288\times$ the energy consumed by LC optimized codes, and $0.19\times$ the energy consumed by the unoptimized codes.

Organization: Section 2 presents a brief background of some of the topics pertinent to this paper. Section 3 discusses the details of AFE and DLBC. In Section 4, we present relevant changes to these transformations in the presence of exceptions. In Section 5, we present an evaluation of DCAFE.

1. Loop-Finish Interchange	
<code>for (S1; c; S2) { finish S3 }</code>	\Rightarrow <code>S1; finish { for (; c; S2) {S3} }</code>
// Say E_s = set of <i>e</i> -asyncs in S3	
// $\neg \exists e \in E_s: c$ has dependence on <i>e</i> .	
// $\neg \exists e \in E_s: e$ has loop carried dependence on S2, <i>c</i> or S3	
2. Finish Fusion	
<code>finish{S1} finish{S2}</code>	\Rightarrow <code>finish{S1; S2}</code>
// S2 has no dependence on any <i>e</i> -async of S1.	
3. Tail Finish Elimination (Simplified)	
<code>finish finish S1</code>	\Rightarrow <code>finish S1</code>

Fig. 2: Existing mini-transformations.

We present a discussion about some of the salient aspects of our work in Section 6 and present a discussion on the related work in Section 7. Finally, we conclude in Section 8.

2. BACKGROUND

2.1. X10

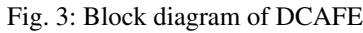
We briefly describe the X10 constructs relevant to this manuscript (see the language manual [Saraswat et al.(2012)Saraswat, Bard, Igor, Tardieu, and Grove] for details). “`async S1`” spawns a new asynchronous task to execute S1. A task can be registered on one or more clocks. “`async clocked(c1, c2) S`” registers the new spawned task on the clocks *c1* and *c2*. Such a task executing `Clock.advanceAll()`, waits for all the tasks registered on *c1* and/or *c2* to execute the barrier `Clock.advanceAll()`. “`finish S1`” waits for all the tasks spawned in S1 to terminate. In X10, each `async` has a unique Immediately Enclosing Finish (IEF), at runtime. Note: statically an `async` may have multiple IEFs.

During execution, when an exception is thrown in an `async`, it is caught by its IEF. The enclosing `finish` waits for termination of the remaining tasks, and then packages all the thrown exceptions as a `MultipleExceptions` object, and throws it again. Note: an exception that occurs in one task (`async`) does not terminate the sibling tasks.

X10 runtime is built around the notion of *workers*. Each worker is assigned a task to execute and can be seen as a software thread. The initial count for workers can be set (typically to to the number of available cores) at runtime, using the environment variable `X10.NTHREADS`. During execution, X10 runtime also tracks the number of *idle-workers* – workers which are assigned no task.

2.2. Finish Elimination

Finish Elimination [Nandivada et al.(2013)Nandivada, Shirako, Zhao, and Sarkar] helps to remove redundant `finish` constructs – `finish` constructs that do not contain *e*-asyncs. For a statement *S*, all the `async` statements (within *S*) whose IEF is not enclosed within *S* are called escaping asyncs or *e*-asyncs [Guo et al.(2009)Guo, Barik, Raman, and Sarkar] of *S*. The ‘Finish Elimination’ optimization repeatedly applies a series of transformations to eliminate the redundant `finish` constructs. Three of their proposed set of mini-transformations (*Loop-Finish Interchange*, *Finish Fusion* and a simplified version of *Tail Finish Elimination*) are relevant to this work. For the sake of completeness, we reproduce these rules in Figure 2. Each transformation may include a set of pre-conditions (shown as comments) necessary to ensure semantics preserving transformation. *Loop-Finish Interchange* is feasible when, neither there is a loop carried dependence between the iterations of the loop, nor the loop condition depends on the *e*-asyncs of S3. This rule can be trivially extended for other looping constructs such as, *while* and *do-while*. *Finish Fusion* merges two `finish` statements, if S2 has no dependence on the *e*-asyncs of S1. *Tail Finish Elimination* eliminates the trivially redundant `finish` constructs.



2.3. Energy Measurements (Intel specific)

Running Average Power Limit (RAPL) [Intel(2014)] is an interface that exposes the Machine Specific Registers (MSRs) to the user application. MSRs facilitate the measurement of the energy consumed by different components of the CPU. The MPES register (MSR_PP0_ENERGY_STATUS) in MSRs stores the total energy consumed by all the cores in a node. We have implemented a function `read_msr()` to read this register, in our generated code. We couldn't find a similar interface for our AMD system.

3. TRANSFORMATION SCHEME

In this section, we discuss two novel optimizations: Aggressive Finish-Elimination (AFE) and Dynamic Load-Balanced loop Chunking (DLBC). We propose a new compiler optimization phase called DCAFE (= DLBC + AFE) that combines these two optimizations. DCAFE (overall block diagram shown in Figure 3) starts by performing a simple *may-happen-in-parallel* (MHP) dependence analysis. For this work, we perform an inter-procedural MHP analysis, as an extension to that of Agrawal et al. [Agarwal et al.(2007)Agarwal, Barik, Sarkar, and Shyamasundar]. The MHP analysis is used to compute the *may-happen-before dependence* (MHBD) [Nandivada et al.(2013)Nandivada, Shirako, Zhao, and Sarkar] information. After the MHP analysis, DCAFE invokes AFE and DLBC optimizations, before doing the code generation. For the sake of simplicity, in this section, we assume that the programs do not throw exceptions. In Section 4, we extend our proposed optimizations to do semantics preserving transformations of X10 programs that may throw exceptions.

3.1. Aggressive Finish-Elimination (AFE)

AFE aims at elimination of redundant `finish` constructs, and expanding the scope of `finish` operations, if possible. AFE consists of eight mini-transformations that aim to pull out `finish` constructs from different methods to their respective call-sites. Three of these mini-transformations have been proposed by Nandivada et al [Nandivada et al.(2013)Nandivada, Shirako, Zhao, and Sarkar] (Figure 2). The rest five transformations (*Async-Finish Interchange*, *Finish-If Interchange*, *Finish Expansion Upper*, *Finish Expansion Lower*, and *Finish-Method Pull*), shown in Figure 4, are new. The necessary pre-conditions for any mini-transformation are specified as comments.

1. Finish-If Interchange
$\text{if}(e) \{ \mathbf{finish} \ S1 \} \Rightarrow v=e; \mathbf{finish} \{ \text{if}(v) \ S1 \}$
2. Finish Expansion Upper
$S1; \mathbf{finish} \{ S2 \} \Rightarrow \mathbf{finish} \{ S1; S2 \}$ // If S1 has no e-asyns registered on clocks.
3. Finish Expansion Lower
$\mathbf{finish} \{ S1 \}; S2 \Rightarrow \mathbf{finish} \{ S1; S2 \}$ // Say $E_s = \text{set of e-asyns in } S1$. // $\neg \exists e \in E_s: S2 \text{ has dependence on } e$. // S2 is not a barrier; S2 has no e-asyns registered on clocks.
4. Async-Finish Interchange
$\mathbf{async} \ \mathbf{finish} \ S1 \Rightarrow \mathbf{finish} \{ \mathbf{async} \ S1 \}$
5. Finish-Method Pull
$ \begin{array}{ll} \text{def } f2() \{ \text{foo}(); \} & \Rightarrow \text{def } f2() \{ \\ \text{def } \text{foo}() \{ & \quad \mathbf{finish} \{ \text{foo}(); \} \\ \quad \mathbf{finish} \ S1; \} & \text{def } \text{foo}() \{ S1 \} \\ \text{// If finish-method has not been already applied on } \text{foo}(). & \end{array} $

Fig. 4: Mini Transformations to facilitate AFE

Finish-If Interchange pulls out a **finish** construct from the surrounding **if** construct. A special case handling the if-then-else statement is shown below:

if(cond)		v = cond
finish S1		finish {
else	\Rightarrow	if(v) S1
finish S2		else S2 }

The switch-case statement is also handled similarly. *Finish Expansion Upper* expands the **finish** scope by pulling a preceding statement S1 in its scope. It requires that S1 does not have any e-asyns registered on clocks. *Finish Expansion Lower* expands the scope of the **finish** construct by pulling in a succeeding statement S1. It requires that (i) there is no dependence between S2 and the e-asyns of S1, (ii) S2 should not be a barrier, and (iii) S2 does not have any e-asyns registered on clocks. The *Async-Finish Interchange* interchanges the surrounding **async** and the inner **finish**. In conjunction with other transformation rules, this rule helps to increase the scope of **finish**. *Finish-Method Pull* lifts a **finish** construct from a method to all its possible callers (obtained by a conservative flow analysis).

The mini-transformations presented in Figure 2 and 4 can be categorized under two heads (a) main rules: transformations to eliminate redundant **finish** constructs, and (b) helper rules: transformations to expose opportunities for applying main rules. For example, Rule #2, and #3 (in Figure 2) reduce the static **finish** operations; and Rule #1 (in Figure 2) and Rule #5 (in Figure 4) can reduce the dynamic **finish** operations; these rules fall in the category of main rules. The Rules #1–#5 in Figure 4 are examples of helper rules. Note: i) Rule #5 is both ‘main’ rule and a ‘helper’ rule. ii) The listed transformations can be applied in any order.

We start applying AFE on the leaf nodes of the call graph and continue applying AFE on their parent nodes (by avoiding the already visited nodes in the call graph, to take care of cycles due to recursion). This process continues till one of the following scenarios is reached: (a) **finish** construct has been pushed to the main method – and no further processing of code is required, or (b) **finish** construct cannot be pulled out of the method, due to dependences, and thus partial rollback takes place: We follow a simple all or nothing strategy for expanding the scope of a **finish**. If the **finish** construct cannot be pulled out of a method then the method is reverted to its original state (the state just before the AFE is applied on this method).

AFE is guaranteed to halt as – (a) the number of call sites are finite, (b) every method is processed only once, and (c) no **finish** constructs are added to the recursive call sites.

Sample Transformation:

We now present the working of AFE on the input code shown in Figure 5(a). Assume that S1, S2, S3, and S4 have no e-asyns. Figures 5(b-h) show the effect of applying AFE on the input code. AFE starts by applying *Finish Fusion* (Figure 5(b)), followed by *Finish-If Interchange* (Figure 5(c)). Then, it applies *Async-Finish Interchange* (Figure 5(d)), *Loop-Finish Interchange* (Figure 5(e)) followed by *Tail Finish Elimination* (Fig-

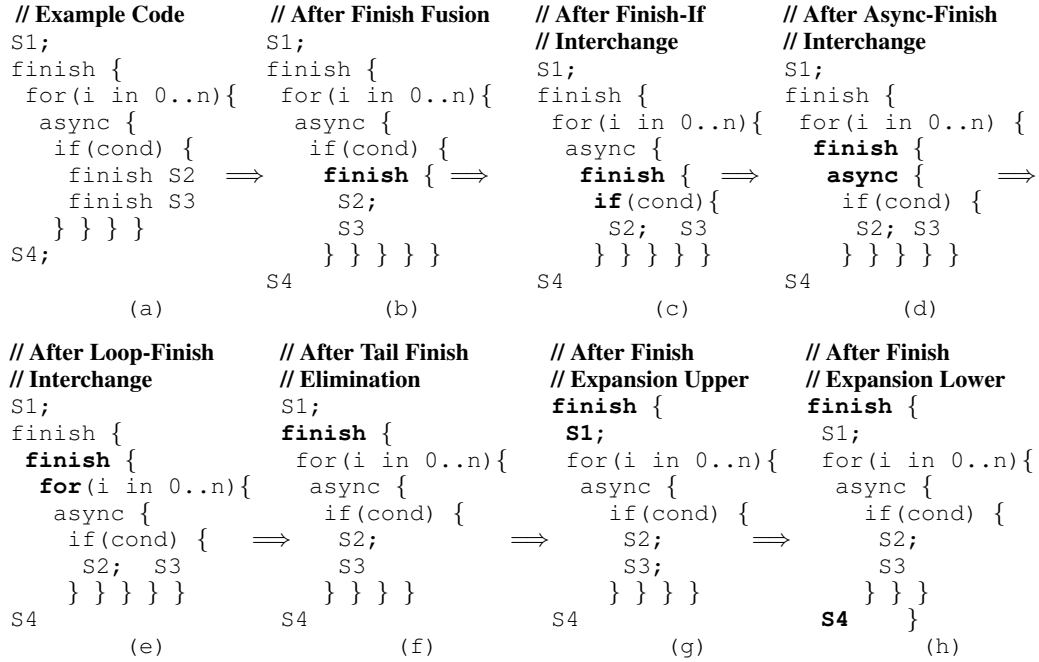


Fig. 5: Applying AFE on a running example

ure 5(f)). Next, it applies *Finish Expansion Upper* (Figure 5(g)) followed by *Finish Expansion Lower* to obtain the code in Figure 5(h).

3.2. Dynamic Load-Balanced loop Chunking

The existing loop-chunking (LC) optimization [Nandivada et al.(2013)Nandivada, Shirako, Zhao, and Sarkar] suffers from a drawback that it may create tasks even when there are no idle workers at runtime. This may lead to significant overheads (especially in case of RTP programs, where it is common to have many tasks created at each level of recursion). Our proposed Dynamic Load-Balanced loop Chunking (DLBC) addresses this drawback through two simple, yet effective strategies: (i) dynamic task creation based on the number of idle workers and load balancing among the workers, and (iii) serial execution if no idle workers are available.

3.2.1. Dynamic task creation and load balancing. One main drawback of LC is that it doesn't distribute the work equally among the available workers. Our chunking policy aims at balancing the load through two simple techniques: (a) dividing the work equally among all the idle workers, and (b) sparing some work for the *current worker* (worker executing the current task).

To highlight the unbalanced load distribution inherent in LC consider the code shown in Figure 1. Figure 1(b) shows the code after invoking LC on Figure 1(a). In Figure 1(b), consider $n=12$ and number of total workers = $nChunks = 4$. Thus, $chunkSize$ is equal to 3, and we create four tasks (to execute three iterations each). Say, excluding the current worker, the other three workers are currently idle. In such a scenario, two of the idle workers execute one task each, and the other idle worker will execute two tasks (six iterations), while the current worker waits at the join point for the spawned tasks to terminate.

In contrast, our chunking policy distributes the iterations equally among all the four workers (including the current worker) – better load balancing. Further, the current worker gets some useful work to perform, before waiting at the join point. Importantly, if $n = 10$, our scheme provides two iterations each to the current worker and an idle worker, and three iterations each to the remaining two workers. Thus, our policy ensures that the current worker not only does some useful work (before waiting at the join point), but also gets the smallest chunk of iterations to execute.

We extend the X10 Runtime (XRX) with a function `Runtime.retIdleWorkers()` that returns the count of idle workers at that instant, at runtime. Our implementation of `retIdleWorkers()` does not use any atomics. So, in a RTP program, it is possible that two tasks may fetch the same value of idle workers, at the

```

1 def nqueens(val n:Int, val j:Int, ...) {
2   var ii:Int=0;
3   var workers:Int = Runtime.retIdleWorkers();
4
5   outer: while(true) {
6     if(workers>0) {
7       val totWorkers:Int = workers+1;
8       val actualn:Int=n-ii;
9       val eqChunk:Int=actualn/totWorkers;
10      val newN:Int=actualn-eqChunk;
11      val rem:Int=actualn%totWorkers+workers;
12      finish {
13        for( ; ii<newN; ) { // “chunked block”
14          val kx = ii+eqChunk+rem/totWorkers;
15          val ni=ii; rem--; ii = kx;
16          async {
17            for(var i:int=ni ; i<kx; i++) {
18              ... /* Checking if none of the queens conflict */
19              nqueens(n, j, ...);
20            } /* async */ } /* outer-for */
21          { // “parent block”
22            for(var i:int=newN; i<size; i++){
23              ... /* Checking if none of the queens conflict */
24              nqueens(n, j, ...);
25            } } /* finish */ } /* if */
26        else for(i=0; i<n; i++) { // “serial block”
27          ... /* Checking if none of the queens conflict */
28          nqueens(n, j, ...);
29          workers = Runtime.retIdleWorkers();
30          if(workers>0 && i<n-2) {
31            ii=i+1; continue outer;
32          } } break; } /* while */ } /* nqueens */

```

Fig. 6: DLBC applied on BOTS Nqueens kernel

same instant. Thus, in practice, the number of tasks created by DLBC may be more than the number of idle workers. But we show that the reduction in task creation is significant enough. Although, the use of atomics looks lucrative, but it leads to substantial overheads.

Overall DLBC consists of five substeps (see Figure 3). It starts by invoking LC. The next step is to introduce some template code that computes the current count of the idle workers and a set of five helper variables: i) `totWorkers`: # idle workers+1, ii) `eqChunk`: minimum number of iterations executed by any worker, iii) `actualn`: number of iterations of the parallel loop to be executed. iv) `newN`: total number of iterations to be executed by the idle workers, and v) `rem`: a temporary variable. This substep also introduces an outer while loop, which is used to avoid unstructured control flow. The third substep of DLBC (Chunked-Block-Modification) modifies the chunked code to enforce the load balancing scheme discussed above. Similarly, the Parent-Block-Generation step introduces code to be executed by the parent thread. For the input code of Figure 1(a), Figure 6 shows the code generated by DLBC. The code computes the number of idle workers and if `workers>0`, the execution continues at line 7. The `finish` body includes a chunked parallel loop (chunked-block: executed by the idle workers), and a serial for-loop (parent-block: executed by the current worker).

3.2.2. Serial Execution. DLBC aims to create tasks only if there are idle workers. Ideally, if there are no idle workers then a new task should not be spawned. In such cases the current task can be asked to complete the remaining job serially. DLBC handles this scenario, by using a simple heuristic: If at the time of task creation the number of idle workers are zero, then the loop under consideration should be executed serially. This heuristic is enforced by invoking the Serial-Block-Generation substep. This substep emits sequential code to be executed when no idle workers are found. Considering the possibility that some workers may get freed up

during the life-time of this serial loop, the generated code checks for available idle workers, after each iteration. And if idle workers are available, the rest of the iterations are divided into `totalWorkers` (= number of idle workers + 1) number of chunks to be executed in parallel.

The “serial block” in Figure 6, depicts the code generated by the ‘Serial-Block-Generation’ substep. An interesting point to note is that At the end of each serial iteration, we check the count of the idle workers. If that count is greater than zero (and at least two iterations are left to execute, to account for the work available for the current worker and at least one of the idle workers), we execute the remaining iterations in parallel. To do so, `ii` is set to the number of iterations that have already been executed, and the control is transferred to line 5; at line 8, `ii` is used to compute the value of `actualn`.

3.2.3. Synchronization Operations and DLBC. Our transformation scheme undergoes a small tweak to handle synchronization operations, in the input code. Consider the input code shown in Figure 7(a) and the code generated by LC in Figure 7(b). The code generated by DLBC is shown in Figure 7(c). Note that the code generated by LC substep will always be of the form shown in Figure 7(b), where the `async` body consists of a series of serial-for-loop separated by `Clock.advanceAll` statement; the serial-for-loop bounds are guarded by a condition.

Similar to the code shown in Figure 6, the code in Figure 7(c) also contains three distinct blocks “chunked”, “parent”, and “serial”. Further, the “chunked block” and the “parent block” have an additional `switch` statement each. Consider the scenario, when there are no idle workers, and the “serial block” is in execution. After executing all the iterations of `S1`, we check for the availability of idle workers, and if available we go back to the “chunked block”, to execute the instances of `S2`. The `switch` statement in the “chunked block” helps skip the code that is already executed in the “serial block”. This selection happens using the variable `phase` whose value matches the number of `Clock.advanceAll` statements executed in the “serial block”. We follow a similar strategy for generating code for the “parent block”.

Note that in the “serial block” we do not check for the availability of idle workers after the execution of each instance of `S1`. This is mainly done to keep a tab on the complexity of the generated code and the overheads.

3.3. Possible Overheads

Overheads due to AFE: The code generated by AFE may incur overheads on two accounts (i) reduction in parallelism: Consider the code transformation shown below:

```
def f2() {
  foo(); bar(); }
def foo() {
  async finish S1 }
⇒
def f2() {
  finish { foo(); } bar(); }
def foo() {
  async S1 }
```

It can be seen that the shift of `finish` construct from the method `foo()` to its call site, inhibits the parallel execution of `S1` and the call to the function `bar` (unless, the scope of the `finish` can be further expanded later to include the call to `bar`). (ii) management of large number of (clocked) activities by a single `finish`: The task executing the join operation (`finish`), performs some book keeping such as, collecting all the exceptions, deallocating resources, de-registering the tasks from the registered clocks (in case of clocked asyncs) and so on. Due to its aggressive nature, AFE entrusts all these bookkeeping works of many `finish` operations (that otherwise may have run in parallel) to one `finish` operation present in a parent task. This may lead to reduction in parallelism and performance degradation.

Overheads due to DLBC: DLBC inserts a number of instructions to do load balancing, and to check for the available idle workers. The resulting overheads can offset the gains, especially if these computations dominate the actual work done by the tasks. In Section 5, we show that all these overheads are compensated by the gains resulting from DCAFE.

4. EXTENSIONS FOR EXCEPTIONS

In this section we extend our proposed techniques to generate semantics preserving code in the presence of X10 exceptions (see Section 2 for a brief introduction). To motivate the impact of exceptions on the presented mini-transformations, consider Rule 2 of Figure 4, being applied on the following example, where `S1` can throw an exception (of type `Ex`).

```

finish { for(var i:Int=0; i<n; i++) {
    async clocked(c) { S1; Clock.advanceAll(); S2; } } }
    (a)

var workers:Int = Runtime.retNthreads();
var chunkSize:Int=(n+workers-1)/workers;
finish {
  for(var ii:Int=0; ii<n; ii+=chunkSize) {
    val ni = ii;
    async clocked(c) {
      var kx:Int=ni+chunkSize; if(kx>n)kx=n;
      for(var i:Int=ni; i<kx; i++) S1;
      Clock.advanceAll();
      for(var i:Int=ni; i<kx; i++) S2; } } }
    (b)

var ii:Int=0, phase:Int=0;
var workers:Int = Runtime.retIdleWorkers();
outer: while(true) {
  if(workers>0) {
    val totWorkers:Int = workers+1;
    val actualn:Int = n-ii;
    val eqChunk:Int = actualn/totWorkers;
    val newN:Int = actualn-eqChunk;
    var rem:Int=actualn%totWorkers+workers;
    finish {
      for( ; ii<newN; ) { //“chunked block”
        val kx:Int=ii+eqChunk+rem/totWorkers;
        val ni=ii; rem--; ii = kx;
        async clocked(c) {
          switch(phase) {
            case 0:for(var i:int=ni;i<kx;i++) S1;
            Clock.advanceAll();
            case 1:for(var i:int=ni;i<kx;i++) S2;
          } } /* async */ } /* outer-for */
        switch(phase) { //“parent block”
          case 0:for(var i:Int=newN;i<n;i++) S1;
          Clock.advanceAll();
          case 1:for(var i:Int=newN;i<n;i++) S2;
        } /*parent*/ } /*finish*/ } /*if*/
      else /*workers <= 0*/ { //“serial block”
        for(i=0 ; i<n; i++) S1;
        Clock.advanceAll();
        workers = Runtime.retIdleWorkers();
        if(workers>0) { phase++; continue outer; }
        for(i=0;i<n;i++) S2;
      } /* else */
    } break; } /* while */
    (c)

```

Fig. 7: Synchronization operations and chunking. (a) Unoptimized version, (b) LC version, and (c) DLBC version.

```

try{ S1; finish S2 => try{ finish { S1; S2;
} catch(e:Ex){...} } catch(e:Ex){...}

```

In the LHS, the exception thrown by S1 is caught by the catch block. However, in the RHS, the finish block catches this exception and in turn throws an object of type

1. Finish-If interchange <code>if(cond) { finish { \Rightarrow S1 } <exlist> } </code>	<code>v = cond; finish { if(cond) S1 } <exlist> </code>
2. Finish Expansion Upper <code>S1; finish { \Rightarrow S2 } <exlist> // ++ // e-asyns in S1 do not // throw exceptions.</code>	<code>var e:Exception=null; finish { try { S1 } catch(e1:Exception) { e = e1; } if(e == null) S2 } <if(e!=null)throw e; exlist></code>
3. Finish Expansion Lower <code>finish { \Rightarrow S1 } <exlist> S2 // ++ // e-asyns in S1 and S2 // do not throw exceptions.</code>	<code>var e:Exception=null; finish { S1; try { exlist } catch(e1:Exception) { e = e1; } if(e==null){ try {S2} catch(ex:Exception) { e = ex; } } } <if(e!=null)throw e;></code>
4. Async-Finish Interchange <code>async { \Rightarrow finish {S1} <> // S1 throws no exceptions.</code>	<code>finish { async { S1 } } <></code>
5. Try-Finish Exchange <code>try { finish { \Rightarrow S1 } <exlist> } catch(e:Ex) { S2 } // e-async in S1 do not // throw exceptions.</code>	<code>var e:Ex=null; finish {try {try {S1} catch(e1:Exception) {throw new ME(e1);} exlist } catch(e1:Ex){e=e1;} } if (e!=null){S2}</code>

Fig. 8: Rules of Figure 4, in the presence of exceptions.

MultipleExceptions. Thus, Rule 2 is not semantics preserving, in the presence of exceptions. We now extend our transformation rules, to address such challenges,

To aid the translation process, we use a temporary finish construct of the form “finish {S1} <exlist>”, where exlist represents a sequence of conditional throw statements. Each entry in exlist is of the form “if (ex != null) throw ex;”. We call exlist the list of *pending exceptions*. This temporary construct is translated away, at the end of the translation process, using the following rule:

finish{S1} <exlist> \Rightarrow **finish**{S1}; exlist;

4.1. AFE in the presence of exceptions

Figures 8 and 9 present the rules for doing AFE in the presence of exceptions. Here, we use ME to refer to the X10 MultipleExceptions class. For brevity, we avoid re-stating the old rules specified in Figures 2 and 4 and use “// ++” to refer to the same.

Figure 8 presents the modifications to our proposed mini-transformations in the presence of exceptions. The *Finish-If Interchange* rule is similar to the one shown in Figure 4. *Finish Expansion Upper* requires that no exceptions are thrown by the e-asyns in S1. The transformed code catches the exception (if any) thrown in S1 and throws the exception outside the finish. The execution of S2 occurs only if S1 throws no exceptions. Similarly, *Finish*

1. Loop-Finish Interchange <pre> for(S1;cond;S2) { finish { S3 }<exlist> } // ++ // e-asyns in cond, S2 // and S3 do not throw // exceptions. </pre>	<pre> S1; var e:Exception=null; var me:ME=null,v:Boolean; finish { for(; ;){ try {v=cond;} catch(ex:Exception) {e = ex; break; } if(e==null && v){ try{S3} catch(ex:Exception){ me=new ME(ex);break;} if(me==null) { try { exlist } catch(ex:Exception) { e = ex; break; } if(e==null){ try{S2} catch(ex:Exception) {e=ex; break;}}}}}} <if(e!=null) throw e; if(me!=null) throw me;> </pre>
2. Finish Fusion <pre> finish{S1}<exlist₁> finish{S2}<exlist₂> // ++ // e-asyns in S1 and S2 // do not throw exceptions. </pre>	<pre> finish { S1 exlist₁ S2 }<exlist₂> </pre>
3. Tail Finish Elimination <pre> finish { finish { S1}<exlist₁> }<exlist₂> </pre>	<pre> try { finish { S1 } exlist₁; } catch(e:Exception) { val me = new ME(e); throw me; }<exlist₂> </pre>

Fig. 9: Rules of Figure 2, in the presence of exceptions.

Expansion Lower requires that no exceptions are thrown by the e-asyns of both S1 and S2; execution of S2 occurs only if S1 and exlist throw no exceptions. *Async-Finish Interchange* requires that S1 does not throw exceptions. It also requires the finish has no pending exceptions. Besides the extensions to the rules from Figure 4, in the presence of exceptions, we need another transformation – *Try-Finish Exchange*. This transformation requires that no exceptions are thrown by e-asyns in S1. For the ease of explanation, we explain the modifications to the *Finish-Method Pull* transformation (of Figure 4), using the following example:

```

def bar() {
  foo(); }
def foo() {
  var e:Ex;
  finish S1;
  <if(e != null) throw e;> }

```

⇒

```

var gex:Ex;
def bar() {
  var e:Ex;
  finish { foo(); e=gex;
  }<if(e!=null)throw e;> }
def foo() { var e:Ex; S1; gex = e; }

```

Here we add a new instance field gex that will store the exception (e) occurring inside the method foo() and will throw e at the call site of foo().

Figure 9 presents the extensions for the three mini transformations of Figure 2, in the presence of the exceptions. Rule#1 ensures that S3 is executed only if no exceptions are thrown by cond, S2 and exlist. Rule#2 ensures that S2 is executed only if no exception is thrown in exlist₁. Rule#3 uses a try-catch block to capture the exceptions thrown by the inner finish and exlist₁, and rethrow it later.

4.2. DLBC in the presence of exceptions

Note that DLBC invokes LC as its first substep. And LC is semantics preserving in the presence of exceptions. It can be easily seen that the code introduced by DLBC does not alter the program semantics (even in the presence of exceptions).

5. EVALUATION

In this section we evaluate our proposed optimizations: AFE and DLBC. We analyze these optimizations on two different systems – a 16 core Intel system (2 Intel E5-2670 2.6GHz processors \times 8 cores per processor) and a 64 core AMD system (4 AMD Abu Dhabi 6376 processors \times 16 cores per processor).

We implemented AFE and DLBC, as whole program optimization techniques, in the x10-2.3.0-linux compiler and present an evaluation of our optimizations using the Native X10 (C++) backend. Each execution time reading is reported by taking an average over ten runs. We evaluate our optimizations on a set of eight RTP kernels (listed in Figure 10), where data parallel loops are the only means of specifying parallelism. The first five are taken from the IMSuite [Gupta and Nandivada(2015)] and the rest three are part of the BOTS [Duran et al.(2009)Duran, Teruel, Ferrer, Martorell, and Ayguade] benchmark suite. Note that, *BFS*, *DST*, and *MST* also have their non-clocked versions in IMSuite. But we chose the clocked versions owing to their added complexity related to barriers.

Figure 10 (first two columns) provides a brief overview of the benchmarks and their respective input data sets. For each BOTS benchmark, we list the input type (e.g., Large, Medium) and for each IMSuite benchmark, we list the input size and a note if we are using the standard input or a modified one. For all the benchmarks (except *DST* and *MST*) we have used one of the standard inputs provided. For *DST* and *MST* we found that the default inputs were not leading to much recursion (as the diameter of the input graph was around 2 or 3), thereby rendering the program nearly non-recursive. To overcome this challenge, we used their respective input generators (provided by IMSuite) to generate larger and denser graphs. In the modified inputs, we cap the maximum number of neighbors of any node to be at 40% of the total nodes; the default inputs have no such limit, thereby generate graphs with very small diameter. For all the benchmarks, the chosen input size was the largest input such that the corresponding input program takes not more than an hour, when run on our 16-core Intel system.

5.1. Dynamic characteristics

Figure 10 includes the dynamic characteristics of the benchmarks under consideration. We executed these kernels on the specified inputs and collected the dynamic counts for the task creation (*async*) and task termination (*finish*) operations. The last two columns of Figure 10, present these characteristics for the unoptimized (UnOpt), Loop Chunking (LC) and DCAFE (= DLBC+AFE) versions.

It can be seen that in comparison to both the UpOpt and LC versions, DCAFE achieves a significant reduction in the number of *async* and *finish* constructs, for *BFS*, *NQ* and *BY* kernels. For *DR*, *HL* and *FL* there is a significant reduction in the number of *async* operations but as AFE is not able to pull out many of the *finish* constructs (due to MHBD), a substantial reduction in the number of *finish* operations is not achieved. In case of *DST* and *MST* as the number of *finish* and *async* operations is low (for the UnOpt and LC versions), the reduction in their counts (because of DCAFE) is also less.

5.2. Comparing DCAFE Vs LC

Figure 11 compares the performance of DCAFE with respect to LC, for varying number of cores (in the powers of two). Figure 11(a) presents the speedups resulting from DCAFE over the LC policy on the Intel system; higher the better. We vary the number of cores and the `X10.NTHREADS` from 1 to 16, in sync (i.e., for simulations on a 4 core setup, we set `X10.NTHREADS` to 4). The performance improvement, for each kernel depends on a varied set of factors – the behavior of the kernel, the

Kernel	Input	Type	#Finish	#Async
Breadth	256	UnOpt	58k	950k
First		LC	31k	379k
Search* (<i>BFS</i>)	(Standard)	DCAFE	1	64
Byzantine	128	UnOpt	276k	3869k
(<i>BY</i>)		LC	276k	3308k
	(Standard)	DCAFE	34	18k
Dijkstra	512	UnOpt	28k	631k
Routing		LC	28k	338k
(<i>DR</i>)	(Standard)	DCAFE	17k	23k
Breadth	2048	UnOpt	3.2k	26k
First		LC	3.2k	1k
Search* (<i>DST</i>)	(Modified)	DCAFE	18	338
Minimum	512	UnOpt	3.1k	6.3k
Spanning		LC	3.1k	2k
Tree* (<i>MST</i>)	(Modified)	DCAFE	1.1k	1.5k
Nqueens		UnOpt	26993k	377901k
(<i>NQ</i>)	(Large)	LC	26993k	377901k
		DCAFE	1	3460k
Health		UnOpt	17516k	630575k
(<i>HL</i>)	(Large)	LC	17516k	210192k
		DCAFE	1636k	2851k
Floorplan		UnOpt	3678k	19244k
(<i>FL</i>)	(Medium)	LC	3657k	19193k
		DCAFE	3619k	1650k

Fig. 10: Benchmark statistics; starred(*) ones have barriers.

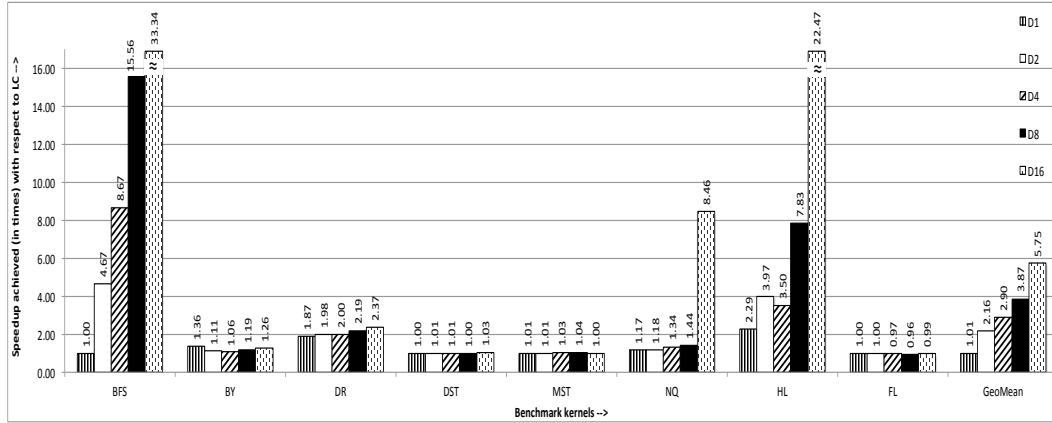
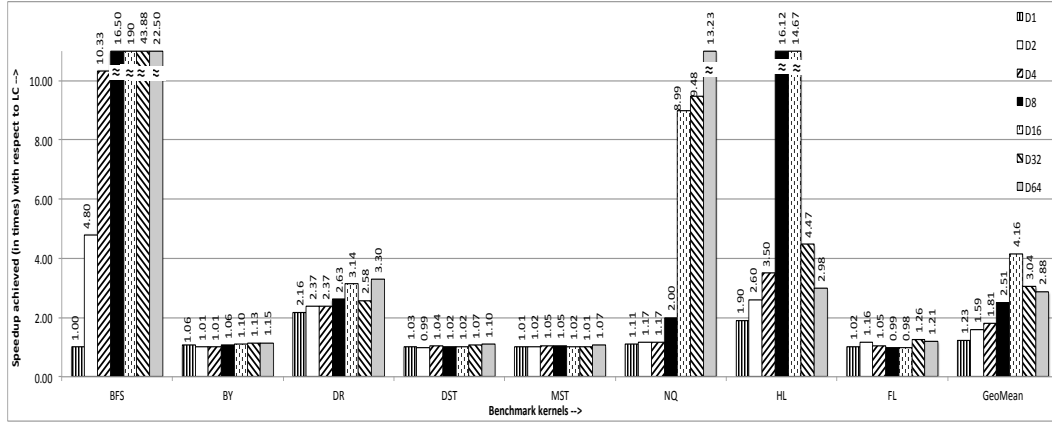
scope for reducing the task creation (`async`) and the task termination (`finish`) operations, the nature of the input, runtime/OS related factors and the hardware characteristics.

It can be seen that for kernels *BFS*, *DR*, *NQ* and *HL*, our technique achieves significant speedups on increasing the number of cores (and thus increasing values of `X10_NTHREADS`). These speedups can be attributed to the varied effects of increased parallelism on LC and DCAFE. As the number of `X10_NTHREADS` increases, LC creates more number of tasks at each level. In contrast, DCAFE creates tasks, only if idle workers are available, and thereby is able to take advantage of the increased number of cores. Thus, comparatively DCAFE has low overheads and synchronization costs, which improve its relative performance. This is one of the main reasons for the sudden peak in case of *NQ* at 16 cores: the execution time for LC increases sharply due to excessive task creation, while the DCAFE version maintains its scalable nature (uniform decrease in execution time), as the number of cores are increased. For *HL* we observe a dip in its performance on moving from 2 cores to 4 cores. This behavior is not due to any deterioration in the performance of DCAFE version or improvement of performance of the LC version for four cores, but because of the comparatively lower performance of the LC version at two cores. We hypothesize this behavior of the LC generated code to the system specific scheduling policies.

A general observation is that when the number of cores are less (1 and 2) the performance gains for DCAFE are insignificant in comparison to LC. This can be attributed to the fewer opportunities for expressing parallelism and the smaller value of `X10_NTHREADS`. For such a setup, both the DCAFE and the LC create few tasks at each level. Thus, DCAFE is not able to record significant task reductions and show gains.

For kernels *DST* and *MST*, DCAFE is unable to achieve significant speedups over LC. This behavior can be attributed to the fewer opportunities for reduction of task creation and termination operations (number of `async` and `finish` operations $< 3k$, see Figure 10).

FL is an interesting kernel where, at times, DCAFE performs worse than LC. In *FL* the task creation occurs inside a doubly nested loop, while the `finish` construct is outside the nested loops. Also, the `finish` construct cannot be eliminated due to dependencies. Importantly, the inner loop

(a) Intel 16-core system; varying runtime configuration Dn , where $n = \text{\#cores} = \text{X10_NTHREADS}$.(b) AMD 64-core system; varying runtime configuration Dn , where $n = \text{\#cores} = \text{X10_NTHREADS}$.Fig. 11: Speedups for varying number of cores; $\text{Speedup} = \frac{\text{execution time of LC version}}{\text{execution time of DCAFE version}}$

does not spawn enough tasks (to optimize to see visible gains). Due to these factors, the DCAFE versions do not have enough scope for improvement, but do more serial work compared to the LC versions (see Section 3.3), which in turn affects its comparative performance.

In case of *BY*, although DCAFE decreases the number of task creation and termination operations by a good measure, the performance gains are minimal. We find that *BY* is the only kernel where the UnOpt version performs better than both LC and DCAFE. This curious behavior results from the nature of *BY* and the density of input. In case of *BY*, similar to *FL*, there isn't much opportunity for loop chunking. Further, importantly, the work done by majority of the spawned tasks in *BY* is negligible. However, compared to the UnOpt version, the LC version introduces additional work in each task (to calculate the `chunks` and so on). And this additional work adds to the time taken by the LC versions. We can see that DCAFE is actually successful in bridging the gap between the performance of LC and the UnOpt to some extent. This could be possible only due to the significant decrease in number of `finish` and `async` operations. However, as discussed in Section 3.3, the overheads of DCAFE amortize the overall performance gains.

Figure 11(b) shows the behavior for the eight kernel benchmarks on the 64 core AMD system. In these plots, we vary the number of cores and `X10_NTHREADS` from 1 to 64, in sync. On increasing the cores from 1 to 16, we observe that the performance of the kernels is similar to that of Fig-

ure 11(a). Except in case of *HL*, where the dip in performance discussed in the context of the Intel system, is not seen here. Thus giving credence to the hypothesis that this may be related to some system level scheduling issues.

On moving from 16 to 32 to 64 cores, we observe interesting characteristics. For all the kernels (except *DR*, *DST* and *MST*), there is an increase in execution time (not shown), for all the three versions UnOpt, LC and DCAFE. This behavior highlights that further gains in execution time cannot be achieved from these kernel versions (especially, for this input), by increasing the number of cores. Thus, the performance gains achieved by the DCAFE versions (shown in Figure 11(b)) are due to the large performance degradation of LC versions, in comparison to DCAFE. For example, DCAFE version for *FL*, which had a slight dip in performance over LC (on 8 and 16 cores), achieves performance (for 32 and 64 cores), due to large degradation in the execution time of the LC versions.

For kernels *DST* and *MST*, as discussed earlier (for the Intel system), the performance gains are not substantial due to less opportunities for exploiting parallelism. In case of *DR* kernel, we observe that the DCAFE version performs better, on moving from 16 to 32 to 64 cores, but the LC version does not follow this trend. The LC version suddenly performs better for 32 cores. This leads to the visible dip in the speedup of DCAFE over LC, for 32 cores.

Overall, with respect to the LC versions, the DCAFE versions achieve speedup in the ranges of $0.1\times - 33.34\times$ (geometric mean of $5.75\times$), on the Intel system, and $1.07\times - 22.5\times$, (geometric mean of $4.16\times$), on the AMD system.

5.3. Performance evaluation of all the proposed techniques

We now compare the performance of Serial, UnOpt+AFE, LC, LC+AFE, DLBC and DCAFE, with respect to UnOpt, in Figure 12. For brevity, we evaluate the kernels only for the largest set of hardware cores (i.e. 16 cores on Intel system and 64 cores on AMD) and `X10_NTHREADS` is set to `#cores`. All the results are normalized with respect to the execution times for the UnOpt versions.

It can be seen that AFE does not reduce the number of redundant `finish` constructs for kernels *DR*, *HL* and *FL*; and hence AFE has no effect (as shown by the numbers of (i) DCAFE Vs DLBC, (ii) LC Vs LC+AFE, and (iii) UnOpt Vs UnOpt+AFE). It can be seen that DLBC and LC+AFE perform better than LC (most of the time), in the context of RTP programs. The exact performance improvement may differ from one kernel to another (depending on the amount of available parallelism). These two techniques when used in conjunction (as DCAFE), perform significantly better compared to all the presented techniques.

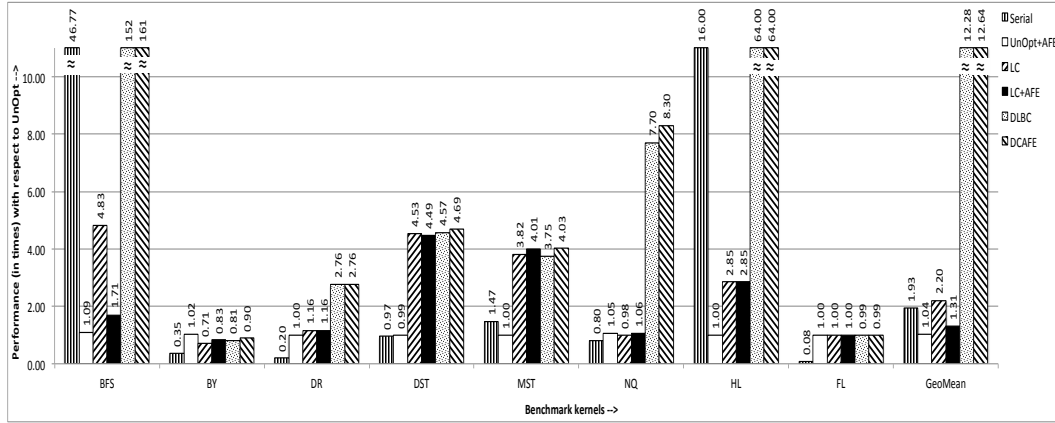
For *DST*, *MST* and *FL*, as mentioned earlier, the performance improvement may not be significant, and can rather have a slight dip, as there is limited scope for task reduction.

In case of *BFS*, we see a significant drop in the performance for LC+AFE on the Intel system, but the plot for the AMD system does not show such a dip. We ran the same benchmark on the AMD system for 16 cores and found that the LC+AFE version showed a similar behavior. We observed that as the number of cores increase the performance of LC+AFE version of *BFS* improves.

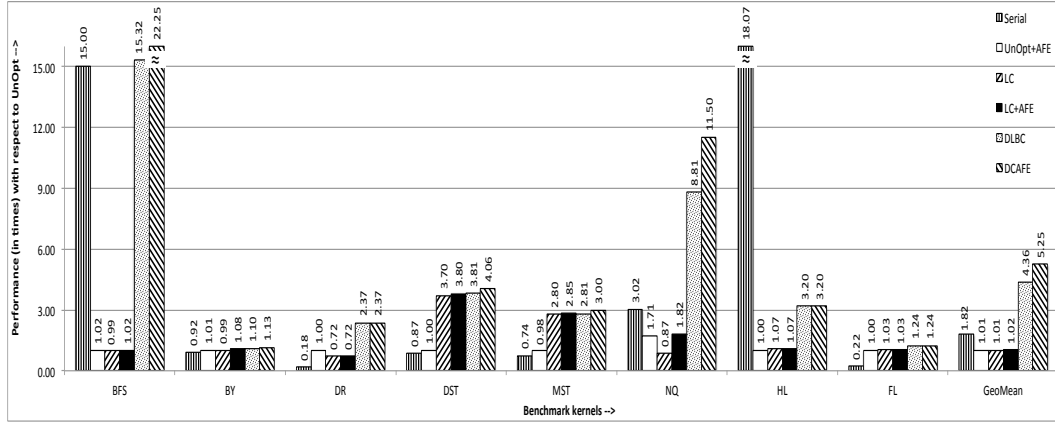
Considering the impact of UnOpt+AFE, it can be seen that the AFE alone is unable to achieve much performance difference, even in the kernels where AFE leads to reduction in the number of `finish` operations. This is due to the overheads arising out of the increased bookkeeping activities (see Section 3.3), that neutralize the gains.

For *BFS*, *HL* and *MST*, the UnOpt versions perform worse than the Serial version, because of the overheads due to parallelization (such as cost for task creation, task termination and barriers). However, DCAFE is able to reduce these overheads and realize gains. *HL* shows an interesting scenario, where DCAFE performs better than Serial in Figure 12(a), but performs poorly in Figure 12(b). On further investigation we found that the DCAFE version of *HL* actually performs better than the serial, when it is run on 8 and 16 cores (on the AMD system). This is consistent with the performance of DCAFE shown in Figure 11(b). A similar reason holds for *NQ*, where the Serial version performs better than the UnOpt version in Figure 12(b), but not in Figure 12(a).

Overall, it can be seen that compared to DLBC, AFE reaps less performance improvements. But we argue that its impact cannot be ignored. Skipping the benchmarks (*DR*, *HL* and *FL*), where AFE



(a) Intel 16-core system, configuration: #cores = X10_NTHREADS = 16.



(b) AMD 64-core system, static configuration: #cores = X10_NTHREADS = 64.

Fig. 12: Comparison of different schemes with respect of UnOpt. Performance of scheme X with respect to UnOpt = $\frac{\text{execution time of UnOpt version}}{\text{execution time of } X}$

did not do any transformation, it can be seen that the impact of AFE is between 1.8% to 45.9%, which we believe is significant.

To summarize: with respect to UnOpt, our techniques LC+AFE, DLBC and DCAFE achieve speedups (geometric mean) of $1.31\times$, $12.28\times$ and $12.64\times$, respectively; compared to these, LC achieves a speedup of only $2.2\times$, on the Intel system. Similarly, it can be seen that on the AMD system LC+AFE, compared to the UnOpt version, DLBC and DCAFE achieve a speedups (geometric mean) of $1.02\times$, $4.29\times$ and $5.25\times$, respectively; compared to these LC achieves a speedup of only $1.01\times$ over UnOpt.

5.4. Energy Consumption

We now discuss the effect of DCAFE and LC on the energy consumption of the benchmark kernels (on the Intel system). We implemented a function `read_msr` that uses the Intel *Running Average Power Limit* (RAPL) [Intel(2014)] interface to read the energy consumption of all the cores of a node. We modify the compiler to emit a call to this function, before and after the execution phase to calculate the energy difference. We couldn't find a similar interface for our AMD system.

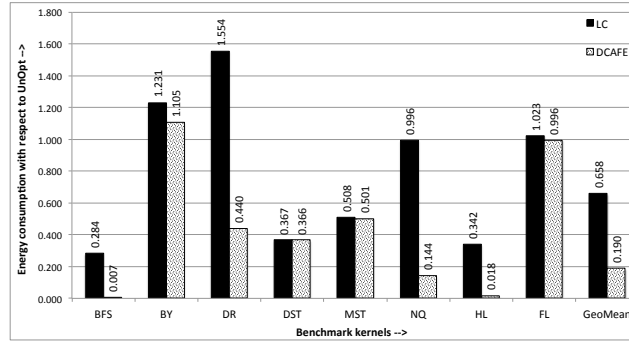


Fig. 13: Energy consumption normalized to UnOpt.

Figure 13 depicts the energy consumed by the LC and DCAFE versions of the eight kernel benchmarks. All the results are normalized to their UnOpt counterparts. It can be seen that for most of the benchmarks, both LC and DCAFE versions show reduction in energy consumption. However, the reduction due to DCAFE is much more than that resulting from LC. Overall, it can be seen that compared to the UnOpt versions, the DCAFE versions consume energy in the range of $0.007\times - 1.105\times$ (geometric mean of $0.19\times$), while the LC versions consume energy in the range of $0.284\times - 1.554\times$ (geometric mean of $0.658\times$). Overall, compared to the LC versions, the DCAFE versions consume energy in the range of $0.026\times - 0.999\times$ (geometric mean $0.288\times$). Thus, on average the DCAFE versions consume 71.2% less energy than the LC counterparts.

We observe that, maximum energy savings is achieved for kernels *BFS*, *DR*, *NQ* and *HL*. These savings directly follow the significant reduction in the execution time, which in turn is due to the reduction in task creation and termination operations for these kernels. On the other hand, for *DST*, *MST* and *FL*, there isn't a significant reduction in the energy consumption, which can be attributed to the less task reduction opportunities available in these kernels. In case of *BY*, compared to the UnOpt version, the energy consumption of both DCAFE and LC versions is higher (follows the trend of the execution time), However, it can be seen that DCAFE reduces the energy overheads of LC to a large extent.

6. DISCUSSION

In this section we discuss some general discussion about our proposed optimizations, their scope and alternatives.

Non-triviality of DLBC: To optimize RTP programs with loops using low level synchronization primitives (like X10 clocks), DLBC includes many non-trivial extensions to LC. These include i) the scheme of executing the loop serially and doing so for a subset of iterations, before proceeding to create parallel tasks to execute the rest of the iterations; and ii) conditionally executing the loop in parallel and ensuring that the parent worker does some useful work, besides waiting for the other threads to join. These proposed extensions give rise to many interesting design choices: i) how/when to switch between serial and parallel codes, ii) procedure to compute the chunking factor, iii) procedure to identify the idle count of worker threads and so on. Besides the particular design choices described in Section 3.2, we tested many other alternatives and finally zeroed in on the most profitable ones. Some of the choices we tested are listed below for pedagogy. (a) *Static cut-off based on the recursion depth* – This scheme stops creating new parallel tasks, once the depth of the recursion crosses a certain static cut-off value (such as, 2, 3, 4, and 5). Thus in this scheme, based on the cutoff, we keep creating parallel tasks even if there are no free workers. Similarly, even if there are free workers, we do not create new parallel tasks after the pre-specified recursion depth. Pros: Simple to implement. Cons: Hard to predict the optimal cutoff and minimize the overheads. Our conclusion after experimentation: Overall inefficient and impractical. (b) *Trade-offs in the*

serial block – To avoid checking for available parallel workers after each serial iteration, we tried the strategy of checking for available workers only after a fixed number of serial iterations (e.g., 2, 3, 4). The main intuition was to allow parallel execution when there are sufficient number of workers. Pros: Reducing the overhead of checking for available workers and waiting for sufficient number of workers. Cons: May miss some chances to parallelize some iterations. Our conclusion after experimentation: The complexity of the additional checks did not pay off. (c) *Minimum number of parallel tasks instead of complete serialization* – DLBC turns to serial code when there are no available free workers. We tried a scheme, where instead of executing the loop in serial, we divided it into two chunks – one chunk executed as part of the current task, and the second one is executed by a new parallel task. Pros: Chances of workers remaining free will be small. Cons: May end up creating more tasks than required. Our conclusion after experimentation: The cons outweighed the pros.

Runtime Optimizations: AFE involves elaborate dependence analysis and code transformation schemes that are non-local in nature (even in the absence of exceptions). Re-casting of AFE as a runtime optimization may seem attractive, but is both non-trivial and can be expensive. Similarly, DLBC requires generation of serial-code from the input parallel code. This process is non-trivial, especially in the presence of deeply nested barriers such as clocks. Both AFE and DLBC are whole program optimizations that have intuitive compile-time implementation and reap runtime benefits.

Scope of AFE and DLBC: AFE and DLBC are not restricted to only X10 and can be applied to other task-parallel languages with similar constructs such as HJ (async/finish) and Chapel (begin/sync). Further, DLBC can also be used in other task parallel languages such as Cilk [Leiserson(2009)] and OpenMP [OpenMP(2008)].

7. RELATED WORK

There have been several works [Cytron et al.(1990)Cytron, Lipkis, and Schonberg; Heinz and Philippsen(1993); Tseng(1995); Ferrer et al.(2010)Ferrer, Duran, Martorell, and Ayguadé; Noll and Gross(2012); Nandivada et al.(2013)Nandivada, Shirako, Zhao, and Sarkar] that aim to reduce the overheads resulting from useless synchronization and join operations. Cytron et al. propose reduction of synchronization constructs by translating input fork-join code to SPMD code with reduced number of barriers. Heinz and Philippsen perform source to source transformations to reduce the barrier synchronization operations in data parallel programs. Their optimizations target the redundant synchronization operations present in the synchronous FORALL statements by converting them into simplified asynchronous FORALL statements with reduced synchronization overheads. Tseng extends the work of Cytron et al. by using a combined fork-join and SPMD model to reduce synchronization overheads. Ferrer et al. exploit the loop unrolling transformation in the presence of task parallel constructs. The authors try to aggregate multiple fine-grained tasks (by unrolling loop) into the larger ones to achieve performance. Noll and Gross propose task reduction and synchronization optimizations for the JIT compilers. The authors propose an optimization that allows merging of small concurrent tasks into a large task. Compared to these, our optimizations eliminate redundant task creation and termination operations in recursive task parallel programs. Further, we present a scheme to do the transformations in a semantics preserving manner, even in the presence of exceptions.

Yonezawa et al. [Yonezawa et al.(2006)Yonezawa, Wada, and Aida] aim at reducing the barrier synchronization operations, by generating efficient communication code for data transfer operations in a distributed application. Similarly, Bikshandi et al. [Bikshandi et al.(2009)Bikshandi, Castanos, Kodali, Nandivada, Peshansky, Saraswat, Sur, Varma, and Wen] propose methods to efficiently execute outer-most finish operations. Nagarajan and Gupta [Nagarajan and Gupta(2010)] use speculative execution to reduce the overheads associated with barriers. We believe that these techniques can be used in conjunction with our proposed AFE, to further increase the performance gains.

Nicolau et al. [Nicolau et al.(2009)Nicolau, Li, Veidenbaum, and Kejariwal] propose optimizations (via code percolation) to reduce the synchronization operations such as `post` and `wait` that are redundant. In contrast, we present techniques to expand the scope of `finish` operations to reduce the number of `finish` operations, especially in the context of recursive task parallel programs.

Our work is most closely related to the work of Nandivada et al [Nandivada et al.(2013)Nandivada, Shirako, Zhao, and Sarkar], who present a framework to reduce task creation, synchronization and termination operations. They specify a set of three techniques – finish elimination, forall coarsening and (static) loop chunking – that generates efficient code for task parallel programs. Compared to their approach, we present an approach to do efficient loop chunking (dynamic) and aggressive finish elimination in the context of recursive task parallel programs.

Narayanan et al. [Narayanan et al.(2005)Narayanan, Chen, Kandemir, and Xie] use classical loop chunking to generate power efficient code. Their transformation distributes equal chunks of iterations on different processors. To the best of our knowledge, ours is the first paper that studies the impact of reduction in task creation and termination operations on the energy consumed.

Loop scheduling [Kennedy and Allen(2002)] has been one of the most popular techniques to efficiently execute loop nests. Some of the popular schemes of loop scheduling are static (dividing the all the iterations equally among the declared workers), dynamic (the iterations are divided into many small chunks and added to a work queue and each free worker takes a chunk from this work queue to execute), and guided (similar to dynamic, but the size of the chunks vary dynamically). Our proposed DLBC method can be seen as a specialization of loop scheduling where i) iterations scheduled to be executed by the same processor are executed sequentially, ii) some iterations of the parallel loop may be executed sequentially, before dividing the rest of the loop iterations among the available workers.

There have been many works [Wilson et al.(1994)Wilson, French, Wilson, Amarasinghe, Anderson, Tjiang, Liao, Tseng, Hall, Lam, and Hennessy; Hall and Martonosi(1998); Yue and Lilja(1996)] that computes and assigns the optimal number of processors / workers to execute a given loop nest and parallelize the loop accordingly. In contrast, we use a simple scheme of chunking parallel loops based on the number of available worker threads (number of chunks = number of available workers). It would be interesting to extend our proposed DLBC with more sophisticated mechanisms to compute the optimal number of worker threads.

Voss and Eigenmann [Voss and Eigenmann(1999)] proposed an inspector-executor model that at runtime decides whether to execute a loop in parallel or serially. The main emphasis behind this scheme is that benefits of executing a loop in parallel may be amortized if the overheads of parallel execution are significant. The authors first try to run a loop in parallel and measure its execution time. They next compare the obtained results with the timed results of the serial version of the loop and decide whether to run the next versions of this loop in parallel or not.

There have been several prior works that control the parallelism based on different kinds of thresholds (all measured at runtime). For non RTP programs, some of the popular thresholds are system load [Kranz et al.(1989)Kranz, Halstead, and Mohr; Certner et al.(2008)Certner, Li, Palatin, Temam, Arzel, and Drach], size of the data structures [Huelsbergen et al.(1994)Huelsbergen, Larus, and Aiken; Aharoni et al.(1992)Aharoni, Feitelson, and Barak] giving an estimation of the time the code to be parallelized may take to execute, and profile based estimated workload in different iterations [Prechelt and H  nssgen(2002)]. For RTP programs, Duran et al [Duran et al.(2009)Duran, Teruel, Ferrer, Martorell, and Ayguade] show the use of a static value of recursion depth as a cut-off for parallelization. Similarly, dynamic cut-offs based on runtime parameters [Duran et al.(2008)Duran, Corbal  n, and Ayguad  ] have also been used for RTP programs. Considering the difficulties in statically determining the appropriate recursion depth, and the overheads in the dynamic approach of Duran et al [Duran et al.(2008)Duran, Corbal  n, and Ayguad  ] (requires additional monitoring threads), we propose a scheme to determine the number of parallel tasks based on the number of available free workers.

Our idea of task creation based on worker availability and “serial block” (in DLBC) can be seen as a compiler based extension of lazy-binary splitting (LBS) scheme [Tzannes et al.(2010)Tzannes, Caragea, Barua, and Vishkin] for RTP programs and programs with synchronization operations. It would be interesting to evaluate the effect of DCAFE on an LBS based runtime scheduler.

8. CONCLUSION

In this paper, we present two new optimizations AFE (“Aggressive Finish Elimination”) and DLBC (“Dynamic Load-Balanced loop Chunking”) to reduce the task creation and termination overheads in recursive task parallel (RTP) programs. These optimizations improve the performance, both in terms of execution time and energy consumption. We implemented DCAFE (= DLBC+AFE) in the X10v2.3 compiler and performed experiments on two different hardware systems (a 16-core Intel system and a 64-core AMD system). Compared to the loop chunking scheme of Nandivada et al [Nandivada et al.(2013)Nandivada, Shirako, Zhao, and Sarkar], DCAFE achieved significant improvements in execution time (geometric mean of $5.75\times$ and $4.16\times$, on the Intel and AMD system, respectively), and substantial reduction in the energy consumption (geometric mean of 71.2% on the Intel system). The significant improvements in execution time and reduction in energy consumption attest to the scope of the proposed optimizations. Though our results are shown in the context of X10, we believe that our proposed optimizations can be applied (with similar effect) to other task parallel languages like OpenMP, Chapel and HJ that admit RTP programs.

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